Sensitivity of regionalized transfer-function noise models to the input and parameter transfer method

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Abstract Monthly shallow water-table depths can be predicted from climate forcings on a large scale by the combination of a transfer-function noise (TFN) model with a parameter regionalization scheme. To investigate the sensitivity of regionalized transfer-function noise (RTFN) models, simulations with different input series and parameter regionalization methods, combined with topographic external drifts, are presented. The input series include the precipitation, precipitation surplus or infiltration calculated by the variable infiltration capacity (VIC) land surface model, and the regionalization methods include those based on a combination of the principal component analysis (PCA) classification or Gaussian mixture model (GMM) clustering, with the external drifts, such as the elevation or terrain slope, generated from digital elevation models (DEM). Verification and cross-validation show that the infiltration series reduces the errors for regionalization by 12.5–18.8%, but cannot improve the calibration. The PCA method outperforms its alternative GMM method for the input series and the external drifts. The combination of the infiltration series and the regionalization method based on PCA classification and elevation produces the best results with respect to the mean absolute error and root mean squared error. The spatial and temporal variations of water-table depths at a macro-scale in continental China are predicted by the combination.

Key words sensitivity; transfer-function noise; regionalization; principal component analysis; water table

Sensibilité de modèles de type fonction de transfert bruit régionalisée (FTBR) aux données d'entrée et aux méthodes de transfert de paramètres

Résumé Les profondeurs mensuelles de nappe superficielle peuvent être prévues sous forçage climatique à grande échelle grâce à la combinaison d'un modèle de type fonction de transfert bruit (FTB) et d'une méthode de régionalisation de paramètre. Pour étudier la sensibilité des fonctions de transfert bruit régionalisées (FTBR), des simulations sont présentées avec plusieurs séries d'entrées et plusieurs méthodes de régionalisation de paramètre, en combinaison avec des dérives topographiques externes. Les séries de données comprennent la précipitation et l'excès de précipitation ou l'infiltration calculée par un modèle de capacité d'infiltration variable (VIC). Les méthodes de régionalisation incluent des méthodes basées sur une combinaison de la classification par analyse en composantes principales (ACP) ou un modèle de regroupement par mélange Gaussien (MMG), avec des dérives externes telles que l'altitude ou la pente topographique, obtenues par analyse de modèles numériques d'altitude (MNA). La vérification et la validation croisée montrent que la série d'infiltration réduit les erreurs de régionalisation de 12.5–18.8%, mais ne permet pas d'améliorer le calage. La méthode par ACP donne de meilleurs résultats que la méthode alternative MMG pour les séries d'entrées et les dérives externes. La combinaison de la série d'infiltration et de la méthode de régionalisation basée sur la classification par ACP et l'altitude donne les meilleurs résultats en termes d'erreur absolue moyenne et d'erreur quadratique moyenne. Les variations spatiales et temporelles des profondeurs de nappe à macro-échelle en Chine continentale sont prévues par la combinaison.

Mots clefs sensibilité; fonction de transfert bruit; régionalisation; analyse en composantes principales; nappe

INTRODUCTION

The shallow water table is an important component of the hydrological cycle and its spatio-temporal distribution is determined mainly by climate conditions, topography, land cover, and the characteristics of soil and aquifer materials. Conversely, the macro-scale fluctuations of the shallow water table result in variations of soil moisture, water and energy balance between the land surface and the atmosphere, which ultimately influence climate (Bierkens & Van den Hurk, 2007; Anyah *et al.*, 2008; Yuan *et al.*, 2008b; Jiang *et al.*, 2009). In addition, groundwater can be a

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source of water for crops during the growing season in rural areas, especially in arid mountain regions. Therefore, prediction of water-table depth is important for research into surface water–groundwater and land–atmosphere interactions (Liang & Xie, 2003; Liang *et al.*, 2003; Hughes, 2004; Yuan *et al.*, 2008b), as well as for agricultural and ecological water management.

Due to the low computation costs and the accuracy of predictions, transfer-function noise (TFN) models have been widely used for water-table estimation, such as those of Tankersley *et al.* (1993), Van Geer & Zuur (1997), Bierkens *et al.* (1999), Von Asmuth *et al.* (2002), Berendrecht *et al.* (2003), Yi & Lee (2004), and Yuan *et al.* (2008a). The statistical methods used for space–time prediction can be divided into three types: (a) the methods starting from a geo-statistical methodology, applying space–time kriging or co-kriging (Van Geer & Zuur, 1997); (b) those based on multivariate time series analysis, where multiple time series are correlated in space; and (c) a combination of methods (a) and (b). One type of combination approach is the use of time series models with regionalized parameters (Bierkens *et al.*, 2001; Knotters & Bierkens, 2001, 2002; Yuan *et al.*, 2008a). The temporal variation is modelled with a time series model, and its parameters are continuous in space. Such an approach is typically useful if data are densely observed in time and sparsely observed in space. For instance, Yuan *et al.* (2008a) proposed a regionalization method based on the Gaussian mixture model (GMM) using a clustering technique to estimate the spatial and temporal variation of shallow water-table depths in continental China, where the observations are limited in space. However, the sensitivity of the simulation results to the input series, regionalization method and external drift needs to be investigated systematically.

First, the TFN models were adopted to predict water-table depths using precipitation as input at monthly time scales (Tankersley *et al.*, 1993), but there are nonlinear relationships between water-table depth and precipitation due to the presence of evapotranspiration and runoff. Therefore, one of the common approaches is to use the precipitation surplus (precipitation minus potential evapotranspiration) as the input when applying the TFN models (e.g. Bierkens *et al.*, 1999; Yuan *et al.*, 2008a). A more complicated method is to generate infiltration input series from physically-based models to reduce the degree of nonlinearity between the input and output series (Yi & Lee, 2004). However, there has been a limited number of studies to detect directly the effects of different input time series on spatio-temporal predictions, which is an important uncertainty when applying the RTFN models because different input series result in different calibrated parameters. Another uncertainty derives from the regionalization method, which is investigated in several studies. For example, Knotters & Bierkens (2002) compared the accuracy of different regionalization methods, and found that the Kalman filter method using DEM data as an external drift outperforms the alternative methods.

In this study, the time series of monthly precipitation, precipitation surplus and infiltration calculated by the variable infiltration capacity (VIC) model are adopted as the input of the TFN models. The parameters are calibrated by Kalman filter combined with the SCE-UA method (shuffled complex evolution method developed at the University of Arizona; Duan *et al.*, 1992, 1993, 1994). The SCE-UA method is an algorithm for automatic calibration of watershed models most widely used over the last 10 years (Shoemaker *et al.*, 2007). The principal component analysis (PCA) classification (Moon *et al.*, 2004) and GMM clustering schemes (Yuan *et al.*, 2008a) are applied to classify continental China into several zones, and the calibrated parameters are regionalized to ungauged areas for the region within the same classified zones by interpolation methods using the elevation or terrain slope as the external drift. The sensitivity of the RTFN models for spatio-temporal prediction of shallow water-table depths based on the combination of the input series, regionalization method and external drift were investigated by cross-validation, and the best one used to predict the spatio-temporal distribution of shallow water-table depths in continental China.

THE VIC MODEL

The three-layer variable infiltration capacity (VIC-3L) land surface model, which is a soil–vegetation–atmospheric transfer scheme that considers both energy and water balance (Liang *et*

al., 1994, 1996), is adopted to obtain the input series of TFN models. The parameterization of evapotranspiration (ET) in the VIC model consists of evaporation from the wet canopy, transpiration from the dry canopy and evaporation from bare soil. Evaporation is βE_p, where β is a function of soil moisture and E_p is the potential evaporation calculated by the Penman-Monteith equation (Shuttleworth, 1993). The transpiration is related to stomatal resistance, which reflects the influence of radiation, soil moisture, vapour pressure deficiency, air temperature, etc. Both saturation excess runoff and infiltration excess runoff are considered in the parameterization of surface runoff, and the soil storage capacity distribution curve and infiltration capacity curve are used to represent the heterogeneity of soil properties (Liang & Xie, 2001). The ARNO method (Todini, 1996) is adopted to describe the baseflow, which is generated from the deepest soil layer. The parameters are calibrated from a limited number of gauged basins, and regionalized to continental China based on climate characteristics and large river basin domains (Xie *et al.*, 2007).

CALIBRATION METHOD

The automatic calibration method based on the Kalman filter and SCE-UA, developed by Yuan *et al.* (2008a), is used to calibrate the parameters of TFN models with different input series. The main procedure for calibration is briefly described as follows:

(1) identify the TFN model, and determine the order of the transfer model and noise model;
(2) represent the identified TFN model in vector notation;
(3) generate random samples for the parameters within the feasible domain;
(4) run the Kalman filter for prediction using the prescribed parameters;
(5) calculate the values of objective function based on likelihood estimation;
(6) rank the calculated values, and partition the evolving and shuffling complexes according to the SCE-UA method; and
(7) repeat steps (4)–(6) until the criterion is satisfied.

Once the TFN model has been calibrated by the method described, it can be used to predict the values of each monitoring well at non-observed time steps and simulate the time series of water-table depths at the same frequency as the input data.

REGIONALIZATION METHODS

To estimate the spatio-temporal distribution of shallow water-table depths in continental China, the calibrated parameters of TFN models are transferred to ungauged areas for the region within the same zones classified by PCA classification (Moon *et al.*, 2004) and GMM clustering (Yuan *et al.*, 2008a) methods.

The PCA is a multivariate statistical procedure for reducing the dimensionality of a data set which consists of a large number of interrelated variables, while retaining as much of the variation of the data set as possible. This is achieved by transforming the original variables into a new set of variables (i.e. the principal components) which are uncorrelated, and which are ordered so that the first few components retain most of the variation presented in all of the original variables.

Let $\boldsymbol{X}$ denote the matrix containing all the observation variables, then $\boldsymbol{XX}^{\mathbf{T}}$ is a symmetric matrix, which can be decomposed into eigenvector and eigenvalue matrices:

$$\boldsymbol{XX}^{\boldsymbol{T}} = \boldsymbol{V\Lambda V}^{T} \tag{1}$$

where $\boldsymbol{V}$ is the eigenvector matrix and $\boldsymbol{\Lambda}$ is a diagonal matrix whose elements are the eigenvalues of the matrix $\boldsymbol{XX}^{\boldsymbol{T}}$.

Principal component loadings can be adopted as a measure of the spatial similarity between the variables and each principal component. This similarity is expressed as a weighted relationship provided by the product of the matrices, $\boldsymbol{V}$ and $\boldsymbol{\Lambda}$, such that:

$$\boldsymbol{L} = \boldsymbol{V\Lambda}^{1/2} \tag{2}$$

where $\boldsymbol{L}$ is the matrix of component loading. Then the observation series can be classified into different types due to the largest value of principal component loading. For example, if the data set can be represented by six principal components, and the second principal component loading is the largest value of a series *A*, then series *A* will be grouped into type two.

The GMM transforms a clustering problem into a probabilistic density estimation problem, which assumes that the data are generated by a mixture of underlying probability distributions in which each component represents a different group or cluster (Bilmes, 1998). The only principle about clustering is to minimize the divergence within each group and maximize divergence between groups. The descriptions of applying GMM clustering method in parameter regionalization are referred to in Yuan *et al.* (2008a).

As the entire grid cells in the study domain are classified into several zones by the PCA or GMM methods, the calibrated parameters in gauged grid cells are transferred to ungauged grid cells as follows:

(1) Where grid cell *i* belongs to one type of zone, find all the gauged grid cells that belong to the same zone as grid cell *i*, and interpolate the parameters of these findings to grid cell *i* by using elevation or terrain slope data based on the DEM as external drift, as described by Knotters & Bierkens (2002):

$$\hat{a}_1(\boldsymbol{u}) = b_0 + b_1 z_{\mathrm{DEM}}(\boldsymbol{u}) + \sum_{i=1}^{n} \lambda_i(\boldsymbol{u})[a_1(\boldsymbol{u_i}) - (b_0 + b_1 z_{\mathrm{DEM}}(\boldsymbol{u_i}))] \tag{3}$$

where $b_0 + b_1 z_{\mathrm{DEM}}(\boldsymbol{u})$ is the drift function depending on the DEM; $a_1(\boldsymbol{u_i})$ are parameter values calibrated on time series observed at location $\boldsymbol{u}_i$ (i = 1, …, n); $\lambda_i(\boldsymbol{u})$ are interpolation weights depending on the location $\boldsymbol{u}$ (the inverse quadratic distance weighting method is used herein for interpolation);

(2) If there are still any grid cells left because they belong to a type that does not include any of the gauged grid cells, we have to interpolate the parameters of all the available grid cells (calibrated or transferred) into these remaining grid cells.

SENSITIVITY STUDY OF RTFN MODELS

Study domain and data sets

The whole of continental China, which has a land area of about 9.6×10^6 km^2, is selected as the study domain. A 42-year (1961–2002) time series of precipitation and temperature was obtained by interpolating the observed data at 753 meteorological stations in continental China. The monthly water-table depth data observed at 571 monitoring wells were supplied by the Ministry of Water Resources and Institute for Geo-Environmental Monitoring in China. The water-table depths of the 571 monitoring wells are less than 10 m because we are only considering shallow groundwater in this study. A description of the locations and sampling frequencies of the monitoring wells is given in Yuan *et al.* (2008a).

Verification of TFN models with different input series

The classical time series modelling procedure consists of three stages: identification, estimation, and diagnostic checking (Box & Jenkins, 1976). In the identification stage, the autocorrelation function and the cross-correlation function are used to determine the order of TFN models. Due to the different characteristics of aquifer and climate in different zones, the order of the models identified by the correlation method varies from one zone to another. It follows from the data analysis for the 571 monitoring wells that the order of moving average parameters of the transfer model for northeastern China (semi-humid region) is lower than that for northern China (semi-arid) and northwestern China (arid), and the order of the models for precipitation input series is higher than that for precipitation surplus and infiltration input series. However, the most sig-

nificant autocorrelation or cross-correlation values both occur at lag one month for most monitoring wells, except for several wells located in arid areas. Therefore, we consider a limited class of TFN model for parameter calibration and regionalization, which can be written as:

$$G_t = c - \frac{\omega}{1-\delta B} P_t + \frac{a_t}{1-\phi B}$$

where G_t and P_t represent time series of the water-table depth and input, respectively; a_t represents the white noise series with constant variance (σ_a^2); c represents the mean water-table depth in the case $P_t = 0$; parameters δ and ϕ represent the memory of water-table anomaly and noise, respectively; and B represents the backshift operator (i.e. $B^n P_t = P_{t-n}$).

Because of the small dimensionality of the stochastic systems considered in this study, it is feasible to obtain the statistics of the parameter estimation errors through Monte Carlo analysis: first, a number of realizations of groundwater data are simulated by the estimated parameter sets and the TFN model; next, the calibrations are performed for each of the realizations, which result in as many estimated parameter sets as simulated realizations; finally, the parameter estimation errors, such as the standard deviation, can be estimated from the parameter sets derived from the realizations (Bierkens *et al.*, 1999).

In order to verify the calibration method with different input series, we selected 23 gauged stations which have at least eight years of observations (sample size ≥ 96) for detailed analysis. The results show that: (a) the standard deviation values of the estimated parameter δ for the precipitation input series are smaller than those for the precipitation surplus series, and the latter are smaller than those for the infiltration series; (b) the standard deviation values of the estimated parameter ϕ for different input series do not present similar characteristics to those of parameter δ, several examples show that the infiltration input series has the smallest standard deviation of the estimated parameter ϕ; (c) the models with $\delta \geq 0.98$ have standard deviation >0.1, except for those in the humid region, but the models with $\phi \geq 0.98$ do not present large deviations; (d) the calibrated parameters ω for the infiltration series are greater than those for the precipitation series or the precipitation surplus series, except for those in the arid region, and the standard deviation of the estimated parameter ω is greater in the arid and semi-arid regions than in the humid and semi-humid regions; and (e) the differences in estimated parameter c for the precipitation, precipitation surplus and infiltration input series are large if the estimated parameters σ_a^2 are large, which indicates that the effects of input series on the estimated mean water-table depths are more obvious for a more uncertain system. In this study, only the natural influences (i.e. precipitation, ET and runoff) are considered in the input variables for the TFN models; therefore, all anthropogenic influences, such as abstraction, drainage or irrigation, will be present in the noise series. To check whether the innovation series a_t are white noise, we plotted the autocorrelations and partial autocorrelations of a_t for the TFN models with high values of parameter ϕ (≥ 0.97) against time (Fig. 1). It is found that the correlation coefficients are less than the significance level, which indicates that the innovation series a_t can be identified as white noise series.

To summarize, the average values of mean absolute error (MAE) over all the (571) monitoring wells for the precipitation, precipitation surplus and infiltration input series are: 24.21, 24.73 and 24.74 cm, respectively. Specifically, 54.3% of the best calibration results belong to the TFN model with precipitation input series, 20 and 25.7% of them belong to the model with precipitation surplus series and infiltration series, respectively. Therefore, the considerations of ET and runoff in the input do not necessarily improve the calibration results. However, comparison of the performance of TFN models with different input series should be verified by using the daily time series in the further study. For example, Yi & Lee (2004) showed that using the daily infiltration input series improved the calibration results for daily water-table depth prediction.

Cross-validation of RTFN models

There are many factors affecting the transfer function, such as precipitation, mean water-table depth, conductance of the top soil, drainage resistance, storage capacity, topography and land

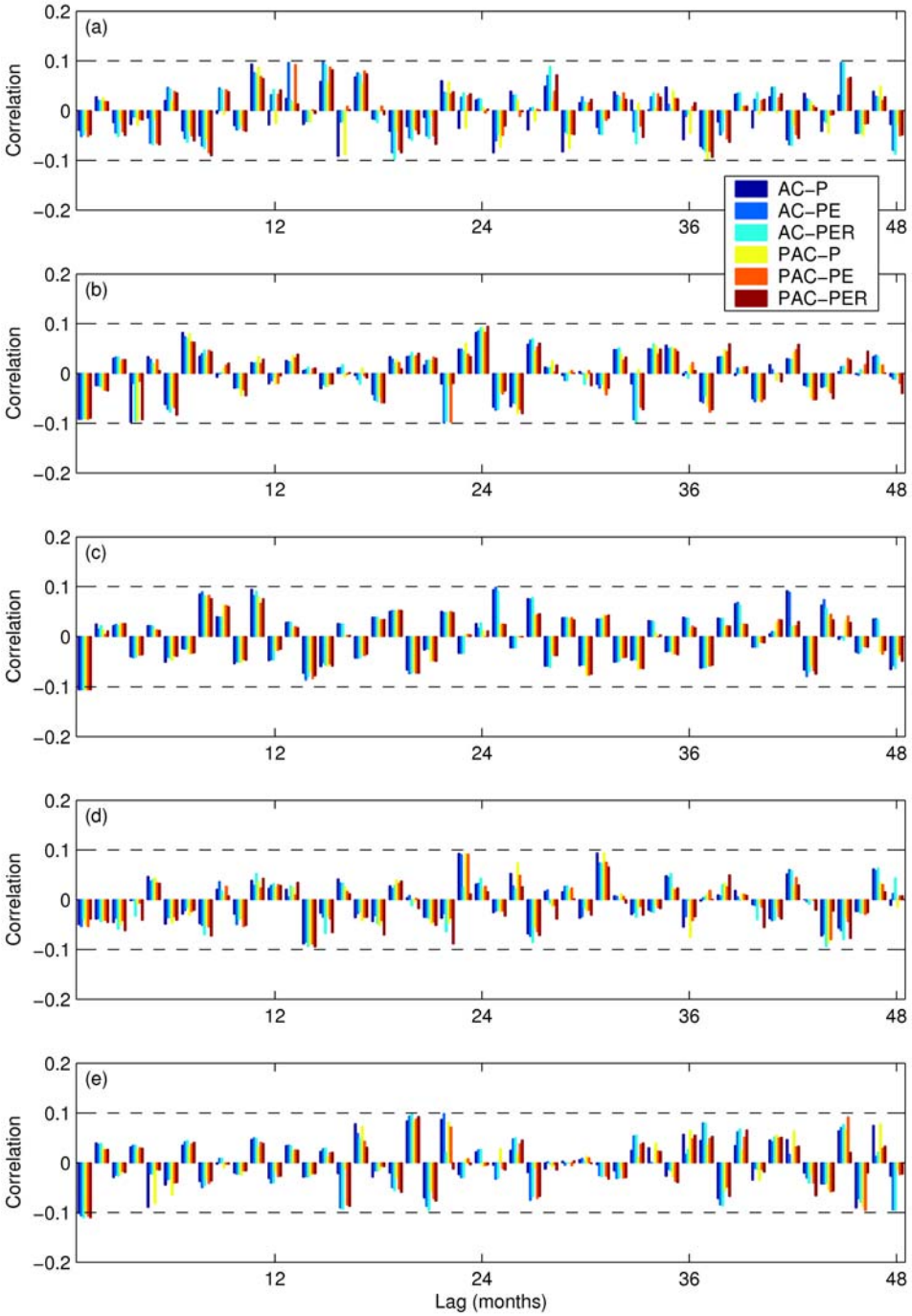

Fig. 1 Autocorrelation and partial autocorrelation of the innovation series a_t for the TFN models with high values of parameter ϕ (≥0.97). P, PE and PER denote the correlations for the precipitation, precipitation surplus and infiltration input series, respectively.

cover, etc. However, precipitation is the most appropriate factor available for regionalization in the present study because it is widely observed in continental China and significantly correlated with shallow water-table depth in the monthly scale. Therefore, we used the grid data of precipitation from 1961 to 2002 and the PCA method to classify continental China into several zones. Since monthly precipitation data for continental China with 4196 grid cells at 0.5° × 0.5° resolution are considered as the input data, the observation matrix has 4196 rows and 504 columns. In this study, 12 components are extracted to explain 52% of the total variation, resulting in 12 different zones

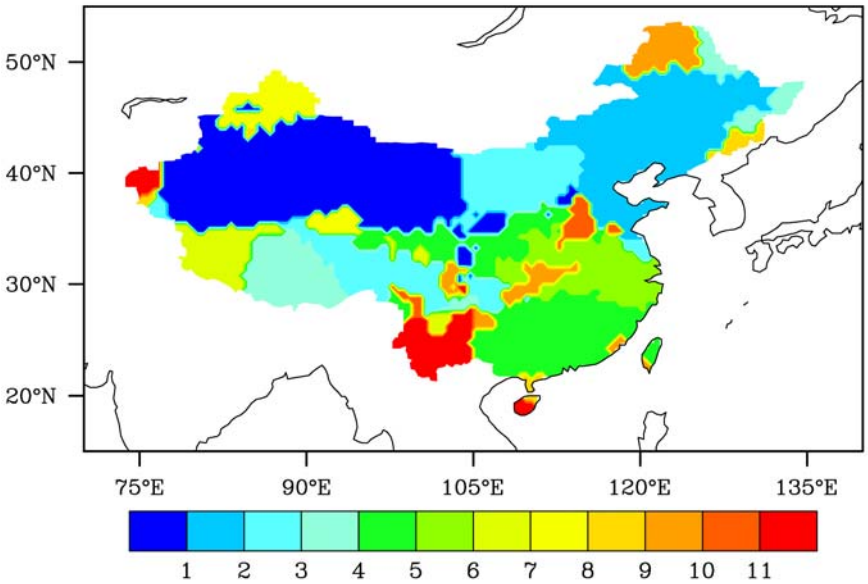

Fig. 2 Classification of precipitation based on twelve principal components in continental China.

in China, as shown in Fig. 2. The alternative regionalization scheme, the GMM clustering method, generates eight zones for continental China (Yuan *et al.*, 2008a).

Considering that there are three kinds of input series, i.e. precipitation, P; precipitation surplus, PE (= P – Evap.); and infiltration, PER (P – Evap. residual), two kinds of regionalization method, i.e. PCA (P) and GMM (G)), and two kinds of external drift (elevation, E; and terrain slope, TS), 3 × 2 × 2 = 12 types of RTFN model are developed for the spatio-temporal prediction of water-table depth. To investigate the performance of different regionalization schemes, water-table depth is predicted at the 571 validation wells by means of a cross-validation procedure. The residuals from the cross-validation procedure are used to calculate the validation measures, i.e. the systematic error (ME), the standard deviation of error (SD), the root mean squared error (RMSE) and the mean absolute error (MAE) described in Knotters & Bierkens (2001). The mean values of validation measures for the 571 validation wells are listed in Table 1. It is found that all types of RTFN model produce reasonable results with respect to the validation measures, and the mean values of RMSE and MAE indicate that: (a) the RTFN model using infiltration as input (PER) performs better than that using precipitation surplus (PE), and the model using precipitation surplus performs better than that using precipitation (P), which demonstrates that more physically-based input series will result in more reliable regionalization results; (b) the PCA method outperforms its alternative GMM method with different input series and external drifts, and the combination of infiltration input, PCA and elevation external drift (PER-P-E) produces the best results among the 12 types of combination; and (c) the results are not sensitive to the choice of external drift.

As mentioned in the regionalization methods, the interpolation is done for each sub-domain separately; therefore, the performance of the RTFN models in each sub-domain should be analysed in detail. Figure 3 shows the cross-validation results over each sub-domain classified by the PCA

Table 1 Mean values of cross-validation measures (cm) for different RTFN models.

	P-P-E	P-G-E	PE-P-E	PE-G-E	PER-P-E	PER-G-E	P-P-TS	P-G-TS	PE-P-TS	PE-G-TS	PER-P-TS	PER-G-TS
ME	0.23	0.10	–0.13	–0.37	–0.09	0.66	–0.01	–0.68	–1.17	–0.44	–0.46	–0.26
RMSE	53.1	55.4	52.6	53.1	45.2	47.3	53.1	54.4	52.1	52.7	46.4	47.6
MAE	45.3	47.1	44.4	44.7	36.8	38.5	45.2	46.2	43.9	44.3	37.9	38.7
SD	32.3	33.5	33.2	33.9	32.4	33.7	32.5	33.4	33.0	33.9	32.8	34.1

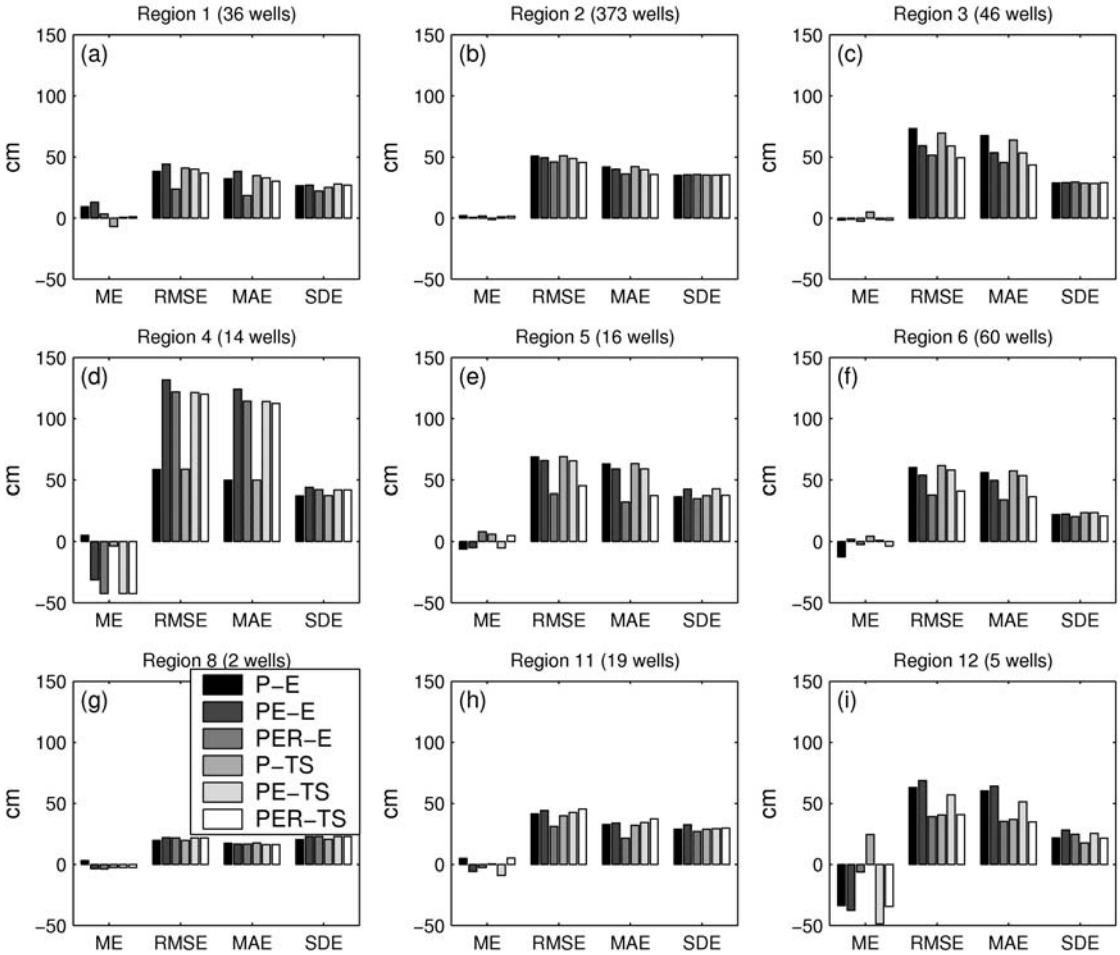

Fig. 3 Cross-validation results of RTFN models with different input series (P, PE or PER) and external drift (E or TS) over each sub-domain classified by the PCA method. Note that regions 7, 9 and 10 are not validated because none of the observations are located in these regions.

method (results over regions 7, 9 and 10 are not presented because of data scarcity). The best results with RMSE and MAE less than 50 cm occur over regions 1, 2, 8 and 11 (Fig. 3(a), (b), (g) and (h)), and the worst results occur over Region 4 (Fig. 3(d)). The RMSE and MAE of regions 3, 5, 6 and 12 (Fig. 3(c), (e), (f) and (i)) are between 50 and 100 cm. Among the nine regions, the RTFN models with the infiltration input series produce the best results with respect to RMSE and MAE except for regions 4 and 11. In fact, Region 4 is a special sub-domain which contains the grid cells located in both northeastern China and the Tibetan Plateau, and the topography and aquifer characteristics are quite different although the precipitation patterns are similar. It results in poor RTFN models with precipitation surplus or infiltration input series (RMSE and MAE > 100 cm) and acceptable models with precipitation input series (RMSE and MAE ≈ 50 cm). The performance of RTFN models in each sub-domain classified by the GMM method is described by Yuan *et al.* (2008a).

SPATIO-TEMPORAL PREDICTION

Based on the cross-validation of the RTFN models with different input series, regionalization method and external drift mentioned above, the RTFN models with infiltration input series (generated from the VIC model), PCA classification method and elevation data (i.e. the PER-P-E combination in Table 1) are adopted to estimate the spatio-temporal distribution of shallow water-

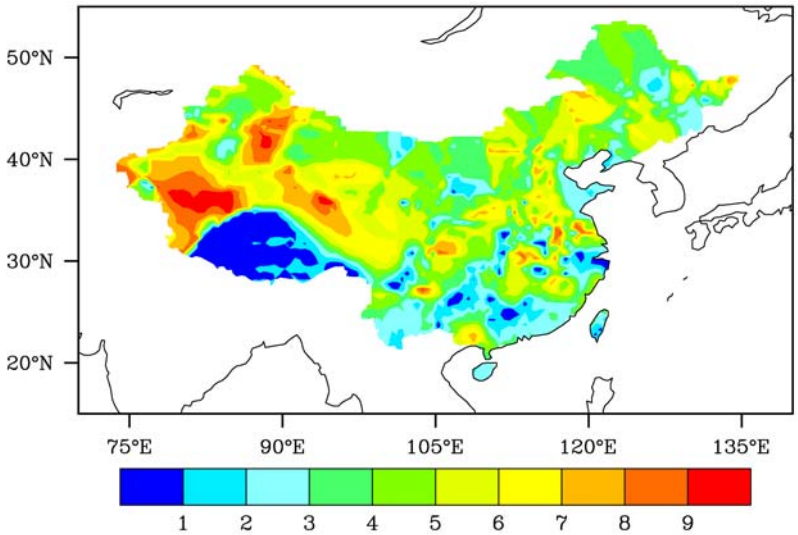

Fig. 4 Estimated mean water-table depths (parameter *c*) in continental China by RTFN model based on infiltration input, PCA classification method and elevation external drift (i.e. the PER-P-E method).

table depth in continental China. Since we only consider shallow aquifers which are less than 10 m and we neglect the impacts of human activity on groundwater in this study, the spatio-temporal prediction results may be less reliable over the mountains, deserts or big urban areas.

Figure 4 shows the spatial distribution of shallow water-table depth in continental China resulting from the PER-P-E method. The spatial pattern of mean water-table depth is similar to that shown by Yuan *et al.* (2008a) over northeastern and northern China where the water-table depths are densely observed, but it is different from that study over western China where the observations are limited. A comparison of the pattern also indicates that spatial prediction of shallow water-table depth at a large scale is a difficult scientific issue because water-table depth is dependent on various factors such as climate conditions, hydrogeological characteristics of soil and aquifer, topography and land cover, and is related to a number of hydrological processes. Once precipitation falls, part of it is intercepted by the vegetation canopy, another part will be lost as surface runoff, and the remainder will infiltrate into the soil and recharge the groundwater by means of the interactions between the unsaturated and saturated zones. Groundwater will discharge as lateral subsurface flow due to gravity drainage or as transpiration because of root uptake. Such recharge and discharge processes vary from one region to another; therefore, the heterogeneity of the land surface conditions increases the uncertainty for spatial prediction of water-table depth.

To further evaluate the robustness of the PER-P-E method, a dry year and a wet year are selected for analysis of the seasonal variability of water-table depth under different climate conditions in continental China. In this study, 1986 is selected as a typical dry year and 1998 as a wet year. Figure 5 shows the distribution of seasonal differences from the long-term average values of the predicted water-table depths in 1986 and 1998 for continental China. The seasonal anomalies are more obvious over southern and northeastern China, where the water table is shallow, than over northern and western China, where it is deep. Northern and southern China present large positive anomalies of water-table depth in June-July-August (JJA) due to the high discharge from ET and insufficient recharge from precipitation during dry years (Fig. 5(c)), while they give the opposite result in wet years (Fig. 5(g)). Specifically, the PER-P-E method, which considers the runoff, successfully captures the negative anomaly of water-table depth in the middle and lower reaches of Yangtze River in JJA of 1998 (Fig. 5(g)), and it is more reasonable than the GMM result described by Yuan *et al.* (2008a). To investigate the fluctuations of shallow groundwater with long memory, the variations in monthly shallow water-table depth averaged over 12 sub-domains classified by the PCA method for a 30-year period (1973–2002) are plotted (Fig. 6). The autocorrelation function values indicate that the memory of areal averaged shallow water-table

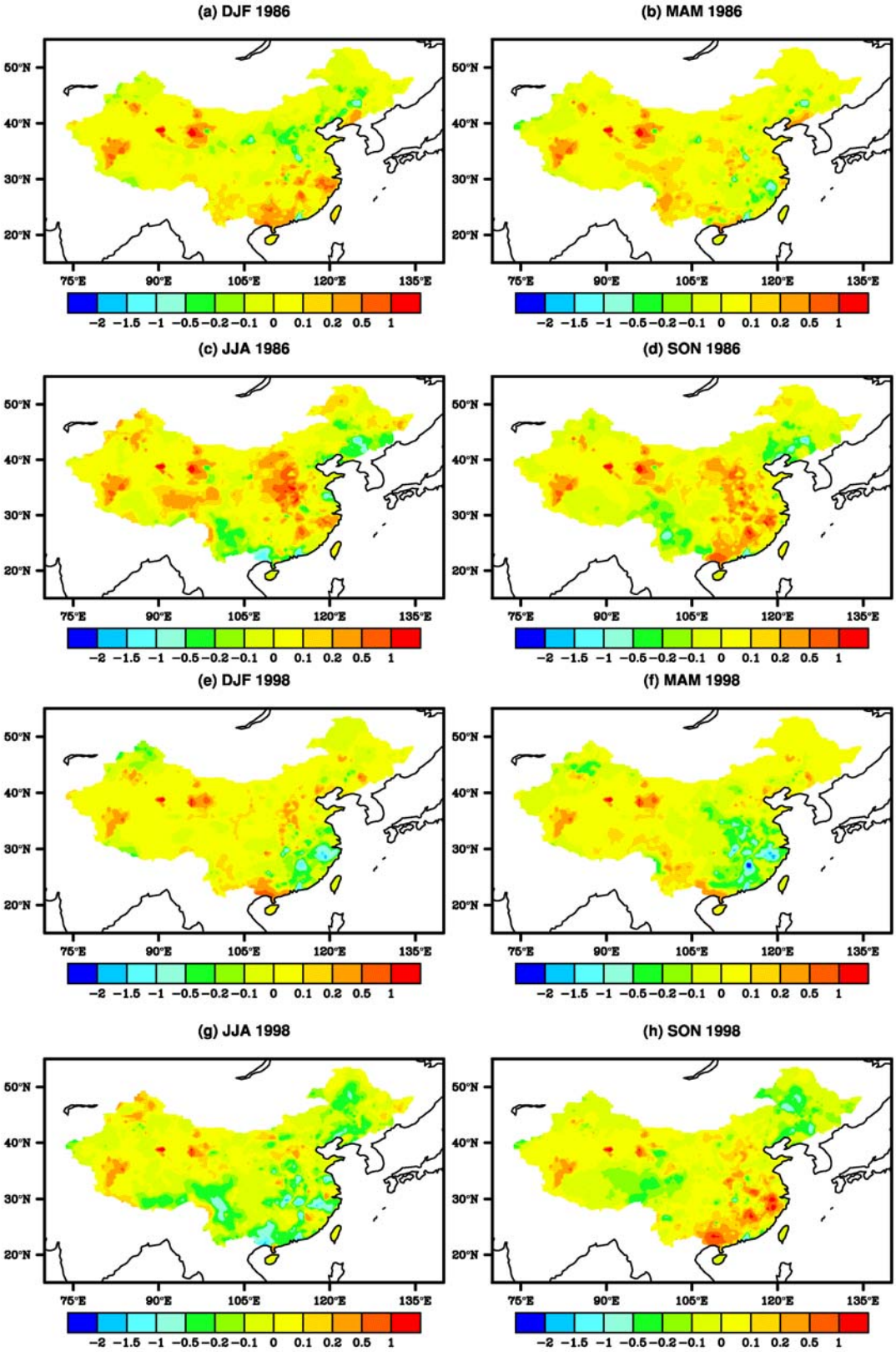

Fig. 5 Seasonal anomalies relative to the long-term average values of the predicted water-table depth (m) for a dry year and a wet year. DJF (December-January-February), MAM (March-April-May), JJA (June-July-August) and SON (September-October-November) denote winter, spring, summer and autumn, respectively.

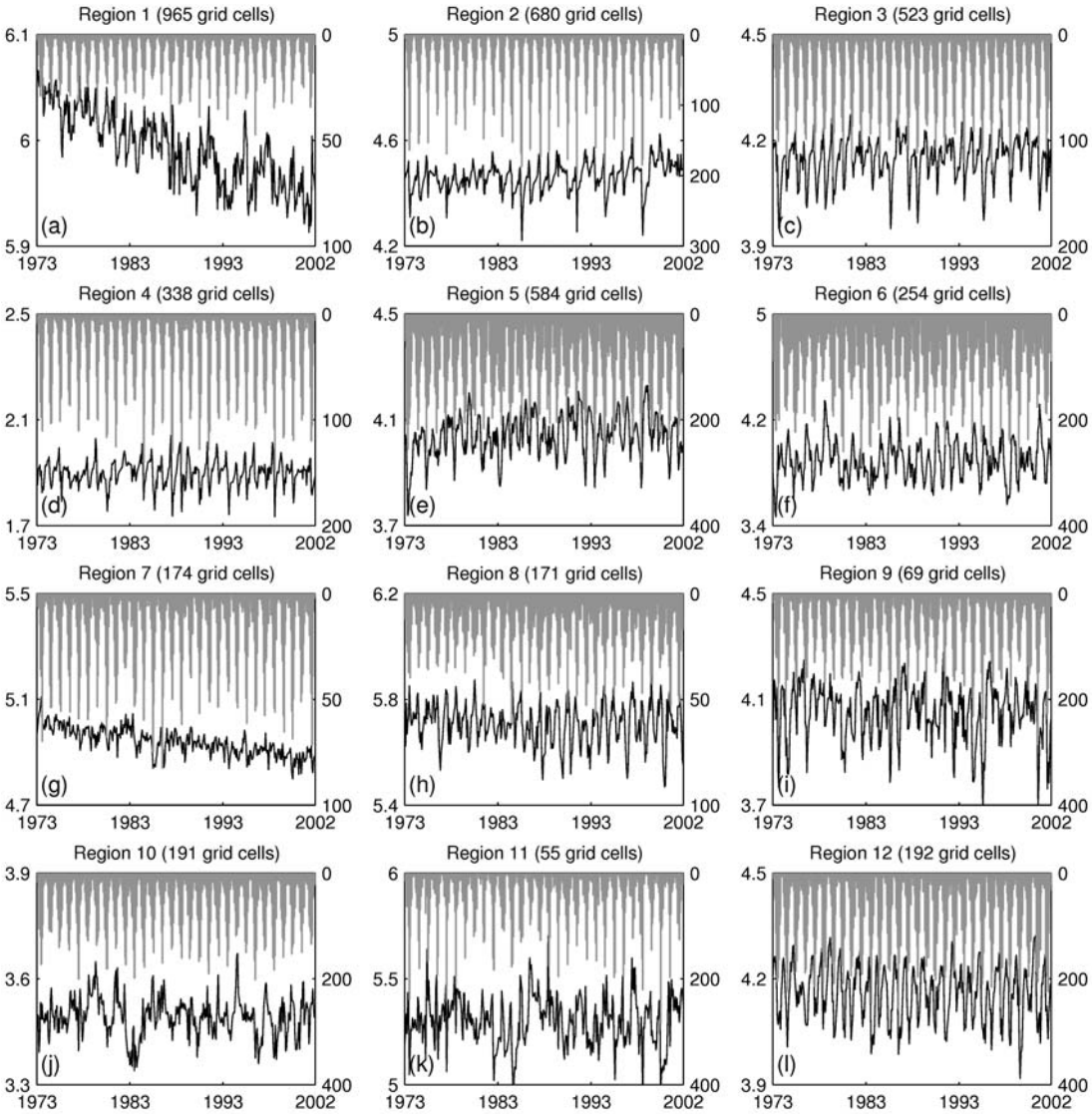

Fig. 6 Decadal variations of monthly precipitation (grey bars, mm/month) and shallow water-table depths (solid lines, m) averaged over twelve sub-domains classified by the PCA method from 1973 to 2002.

depth series varies from two to six months (two months for regions 3, 4, 8 and 12; three months for regions 5, 6 and 9; five months for regions 2 and 11; and six months for Region 10), except for regions 1 and 7 which are located in western China. Figure 6 (a) and (g) shows that the fluctuations in water-table depth over regions 1 and 7 persist for many years, and the resulting groundwater memory is about 15 and 18 years, respectively.

To summarize, the proposed scheme reasonably reflects the response of spatio-temporal variations in shallow water-table depth to climate change in continental China.

CONCLUSIONS

The sensitivity of regionalized transfer-function noise (RTFN) models for predicting the shallow water-table depths in space and time was investigated by comparing time series simulations with different input series, parameter regionalization methods and external drifts. The input series were precipitation, precipitation surplus or infiltration calculated by the VIC model, and the resulting

MAE for all the calibrated monitoring wells were 24.21, 24.73 and 24.74 cm, respectively. This indicates that using the infiltration series in the TFN model does not improve the calibration at the monthly time scale. However, cross-validation shows that the infiltration series reduces the error of RTFN models by 12.5–18.8% with respect to MAE and RMSE, demonstrating that more physically-based input will result in more reliable spatio-temporal predictions. The RTFN models using the PCA classification method outperformed those using the GMM clustering method, but their performance was not sensitive to the choice of external drift. Finally, the combination of infiltration input series, PCA regionalization method and elevation external drift, which was found to be the best RTFN model through cross-validation (RMSE and MAE are 45.2 and 36.8 cm, respectively), was applied to simulate the spatio-tempral distribution of shallow water-table depth in continental China.

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